SPATIAL REPRESENTATION IN THE SOCIAL INTERACTION POTENTIAL METRIC: AN ANALYSIS OF SCALE AND PARAMETER SENSITIVITY

by

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ABSTRACT

The Social Interaction Potential metric measures urban structural constraints on social interaction opportunities of a metropolitan region based on the time-geographic concept of joint accessibility. The current implementation of the metric utilizes an interaction surface based on census tracts and the locations of their centroids. This has been shown to be a shortcoming, as the metric strongly depends on the scale of the zoning system in the region, making it difficult to compare the Social Interaction Potential metric between metropolitan regions. This research explored the role of spatial representation in the Social Interaction Potential metric, and identified a suitable representation that allows for error-free comparison between regions while retaining cost-effectiveness with respect to computational burden. We also reported on findings from an extensive sensitivity analysis investigating the Social Interaction Potential metric's input parameters such as a travel-flow congestion factor and the length of the allowable time-budget for social activities.

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1. INTRODUCTION

Origin-destination flow matrix data are widely used by transportation researchers to assess social, economic, and environmental impacts of transportation and land use systems. In one example, in order to investigate how transportation systems affect opportunities for face-to-face social interaction, a regional-scale measurement of face-to-face social interaction, the social interaction potential (SIP) metric, was developed by computing origin-destination flow and travel time matrices (Farber, Neutens, Miller, & Li, 2013). As will be shown more formally below, the internal workings of the SIP metric require calculations of space-time prism intersections between pairs of commuters in a region. However, the basic formulation put forward in Farber et al. (2013) does a poor job of approximating the volume of the space-time prisms' intersection. In light of this shortcoming, the SIP formula highly depends on the scale and method of dividing the region, invoking consideration of the Modifiable Areal Unit Problem. This makes it difficult to compare SIP between metropolitan regions as each region is composed of a unique number of census tracts of varying sizes and spatial arrangements.

To address this shortcoming, in this research, we redefine the SIP metric using a more precise grid-based procedure for calculating the space-time prism intersection volume. We also conduct experiments to help us determine the most accurate grid resolution while trying to minimize computational burden. We implement the new definition of the SIP metric, and conduct experiments to test the sensitivity of the metric to several parameters, including scale, congestion, and the time-budget for social activities.

The remainder of the paper is organized as follows. In the next section, we provide a brief literature review discussing the background of the study, and introduce the reader to the new definition and implementation of a grid-based social interaction potential. In section 3, we describe the methods used to conduct our research, including the design of our research experiments, computational strategies, and data sources. The results of our experiments are put forward in section 4, followed by a discussion and conclusions in section 5.

2. BACKGROUND

2.1 Literature Review

When it comes to whether geography can influence people's behavior, the previous literature focuses more on the effects of local-scale urban forms rather than regional-scale spatial structures. For example, Ewing (1997) discussed how sense of community affects social interaction activity patterns by following Jacobs' (1961) idea that mixed land-use can encourage people to participate in social interaction by increasing citizens' sense of community. Following this idea, Freeman (2001) indicated that the growing ownership of automobiles and the privatization of open space constrain people's ability to contact each other. Similarly, Farber and Páez (2009) used multivariate regression to analyze the relationship between automobile use and social activity rates and durations, showing that people who only use automobiles to travel are less likely to participate and spend less time in social interaction activities. Farber and Páez (2011) validated the result of the previous research; drivers were less likely to participate in out-of-home social activities when compared to nondrivers in Canadian cities observed between 1992 and 2005. Although the above research demonstrates that local spatial condition, automobile dependence, and automobile oriented land use patterns can impact some of the patterns of social activity participation, Farber et al. (2013) put forward a time-geographic indicator that measures social interaction opportunities at a regional scale that can be linked to a city's land-use patterns and commute flows.

2.1.1 Time Geography

Before we introduce the regional-scale social interaction potential metric, we will first review its theoretical basis - time geography. The time geography concept discusses three types of space-time constraints that limit our activity space (Hägerstrand, 1970). First, capability constraints are related to the physical constraint of being human and are usually reduced to measures of travel speed. Second, coupling constraints occur because people have to meet each other at certain times and certain locations, and third, authority constraints are related to the spatial limitation of laws and authorities. Time geography investigates how these space-time constraints affect our everyday activities. With empirical time diary data, Cullen and Godson (1975) applied the time geography concept to analyze spatiotemporal and sequencing characteristics of activity patterns. According to the basic theory and the empirical application of time geography, the geographic constraints impacting human activities can be investigated using transportation, time use, and land use data.

To measure time geographical constraints and to investigate the movement opportunities of people, Lenntorp (1976) introduced the three-dimensional geometric concepts of the space-time path and space-time prism (STP). These three-dimensional concepts result in plots where the time dimension of people's activities appears on a vertical z-axis, and the spatial dimension is compressed to two-dimensional space that is represented by the planar x and y axes. Within this three-dimensional space, the space time path represents all the consecutive space/time coordinates passed by an individual. Although there might be many possible paths, only one of them will be taken. Given a space-time start point, a space-time end point, and the individual's travel speed, all three-dimension space-time points that can be reached by an individual are represented by the space-time prism, also called the potential path space.

2.1.2 Spatial Representation of Time Geography in Geographic Information Systems

With the growth of geographic information systems (GIS) in the study of geography, and starting with Miller (1991), there are many examples for how time geographical concepts can be digitally represented in a GIS. For example, Miller (1991) demonstrated the network-based potential path area (PPA) of space-time prisms that was not defined in continuous, two-dimensional space. The space-time prism can also be represented by the coverage data model showing if the activity system is feasible or unfeasible (Miller, 1991). Kwan and Hong (1998) proposed a method that could be easily implemented in GIS by using the concept of a cognitive feasible opportunity set (CFOS), the spatial representation of the potential destinations in the potential path space. In addition, the GIS data model was refined by considering segment-specific travel speed and some other details of individuals to make sure that the representation of the space-time prism is individual based, facility based, and context specific. When defining the measurements in time geography, including the space-time path, prism, composite path-prisms, stations, bundling, and intersections, Miller (2005a) stated the prism as a parametric function of time by assuming a constant maximum velocity. Neutens, Van de Weghe, Witlox, and De Maeyer (2008) constructed an analytical description of three-demensional network-based space-time prism that can be imported to Computer-aided design (CAD) as a three-dimensional object by using isochrones defined by a set of connected points at equal travel times. The time geography concept with the terminologies of space-time path, space-time prism, and potential path area/space will be the theoretical foundation of the proposed research that investigates potential social contact opportunities in the city.

2.1.3 Time Geographic Measurements of Accessibility

One of the most widespread uses of time geographical concepts is in the measurement of accessibility. Combining pace-time prisms, spatial interaction theory, and utility-based accessibility measures, Miller (1999) developed a measure of space-time accessibility benefits within a transportation network. To apply the concept of space-time accessibility measures, Kwan (1999) analyzed the gender differences in accessing urban opportunities by investigating the opportunities in the daily potential path area (DPPA). The result of this study indicated that women have lower levels of accessibility to urban opportunities. Miller and Wu (2000) implemented space-time accessibility by developing GIS software that could compute space-time measures. The main technique of the implementation is generating an extended shortest path tree rooted at network nodes corresponding to flexible activity locations. Kim and Kwan (2003) improved this measure by representing the opportunities by the feasible opportunity set and considering a set of possible activity duration. Ettema and Timmermans (2007) further developed this accessibility measurement and it could be viewed as an alternative measurement of individual's space-time constraint under the assumption of time budget and mobility constraints.

2.1.4 Time Geographic Measurements of Joint Accessibility

The papers described above only apply to measuring accessibility to static features in the urban environment, but what about measuring accessibility of one person to another?

We can implement time geographical concepts such as the space-time prism and the space-time path to measure the spatial and temporal factors that constrain social activities. Space-time accessibility measures that use the concept of space-time prisms have a mature definition and several applications. Several researchers have used the time geography theory to discuss the relationship between space-time constraints and human activities. Miller (2005b) discussed the necessary space-time conditions for human interaction by using the measures of space-time path and space-time prism and discussed the human physical interaction by investigating their path-path, path-prism, and prism-prism intersections. Yu and Shaw (2008) explored potential human activities in physical and virtual spaces. A three-dimensional spatial-temporal GIS design has been developed in this research to use space–time prisms to support the representation, visualization, and analysis of potential human activities and interactions in physical and virtual spaces using the prism representation. Lee and Kwan (2011) discussed the visualization of social-spatial isolation based on human activity patterns and social networks in space-time. Visualization techniques of 3D space-time paths, time windows, 3D activity density surfaces, and ring-based visualizations of social networks were used to display the patterns of social interaction. In order to measure the accessibility of activities that need two people's participation, Neutens, Schwanen, Witlox, and De Maeyer (2008) defined a measure of joint space-time accessibility that considers activities involving multiple persons and the group decisions needed to negotiate the extra coupling constraints that impose restrictions on the activity location choice set and on activity participation in general. When discussing joint accessibility, Neutens, Schwanen, and Miller (2010) began to use time geography and space-time prisms to investigate coupling constraints and joint activity participation and argued that collective activity decisions are the outcome of a complex process involving various aspects of timing, synchronization, and social hierarchy. Yin, Shaw, and Yu (2011) developed an analytical framework using the space-time prisms and a space-time GIS to examine the dynamic changes of potential face-to-face meeting opportunities between two people when people have advanced communication tools. To measure social interaction opportunities at the regional scale and to explore the relationship between urban infrastructure and social interaction opportunities, Farber et al. (2013) developed the Social Interaction Potential (SIP) metric based on the space-time joint-accessibility concept. In this research, we plan to refine the SIP metric and build a tool that computes this SIP through aggregated home-to-work data and GIS-based street network data.

2.1.5 Modifiable Area Unit Problem

When implementing SIP based on space-time prisms and joint-accessibility measures in a GIS, we rely on aggregated data to compute the result because individual-level data for an entire region is seldom available. While dealing with aggregated data reduces the computational burden of the task, the modifiable area unit problem (MAUP) quickly arises when we compare the approximations of space-time prisms and measurements of joint accessibility using data with different aggregation patterns and scales. This MAUP was proposed by Openshaw (1984) by defining it as two types of effects. The scale effect is the variation in results that can often be obtained when data for one set of areal units are progressively aggregated into fewer and larger units for analysis. The second effect is the aggregation problem that is defined as any variation in results due to the use of alternative units of analysis when the number of units is held constant. The approach used to analyze the patterns of variation when changing the aggregation type and scale, essentially constituting a parameter sweep, can be used in this study to investigate the impact of aggregation on the estimation of SIP.

2.2 The Social Interaction Potential Model

In order to use the time geography concept to quantitatively measure the social interaction opportunities in a metropolitan region, we made a series of assumptions for social activities we propose to investigate. We assume that all workers in the study region leave from their work place by automobile at the same time, and all of them should arrive at home in a fixed amount of time, which is defined as an after-work time budget. The research only targets on the social interaction activities organized by the two workers at static locations during this after-work time budget. These assumptions can be loosened if we are able to get detailed time use data and travel survey data.

2.2.1 Current Definition of Social Interaction Potential

The current definition of social interaction potential on a metropolitan scale focuses on a social activity within a single, after-work time budget. We assume that the citizens in a metropolitan area all have an after-work time budget that equals $b > 0$ in which they can perform a social contact activity. For the region that consists of N administrative zones, $Z_1, Z_2, \ldots, Z_N$, let t_{ab} be the required travel time from Z_a to Z_b. Then,

$$A_{ij}^{k} = \begin{cases} (b - t_{jk} - t_{ki}) & \text{if } b \geq t_{jk} + t_{ki} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

is the amount of time available for an after-work social activity at Z_k for an individual who lives in Z_i and works in Z_j.

Suppose the individual who lives in Z_i and works in Z_j attempts to participate in a social activity at location Z_k with another individual who lives in Z_q and works in Z_r. In this case, the amount of time available to them for the activity at Z_k is:

$$A_{ijqr}^{k} = \begin{cases} \max\left(0, \min(b - t_{ki}, b - t_{kq}) - \max(t_{jk}, t_{rk})\right) & \text{if } A_{ij}^{k}, A_{qr}^{k} \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where $\max(t_{jk}, t_{rk})$ is the beginning of the overlapping time period, $\min(b - t_{ki}, b - t_{kq})$ is the ending of the overlapping time period, and the $\max(0,\cdot)$ function excludes the case where the two individuals have nonoverlapping time availabilities at Z_k.

It follows that the total social interaction potential for these two individuals across the N zones of interaction can be measured as:

$$A_{ijqr} = \sum_{k=1}^{N} A_{ijqr}^{k}. \quad (3)$$

The value of A_{ijqr} can be thought of as an approximation to the volume of the intersection between the time-space prisms of the two individuals. To compute the social interaction potential of a region in the real world with home-to-work journey datasets aggregated into zones, we use commute flow probabilities, $P_{ij} = \frac{r_{ij}}{R}$, that is the percentage of workers in the region that travel from zone i to zone j, where $R = \sum_{i,j} r_{ij}$, and r_{ij} is the number of workers who live in Z_i and work in Z_j. Accordingly, we get the following SIP metric that could be computed using home-to-work journey data:

$$SIP = \sum_{i} \sum_{j} \sum_{q} \sum_{r} \sum_{k} A_{ijqr}^{k} P_{ij} P_{qr} \quad (4)$$

One issue with this formulation is that $\mathrm{A}_{\mathrm{ijqr}}$ is not a good approximation of the volume of a space-time prism intersection. The definition fails to consider that the patterns of the zoning system might influence the approximation results, specifically because the areas of the activity locations are not used in the computation of the volume. Thus, $\mathrm{A}_{\mathrm{ijqr}}$, is really just a summation of time windows, and the value of SIP will be arbitrarily larger or smaller depending on the number of zones in the region. According to the modifiable area unit problem (MAUP) proposed by Openshaw (1986), the result might change if the data were aggregated into fewer and larger units for analysis, or if the units of analysis were altered when the number of units is held constant. Because in the United States, the Census Bureau and local planning agencies use different ways to divide regions into census tracts, we need a new definition of the social interaction potential metric in order to increase the accuracy of the prism intersection volume calculations and to make the metric more comparable between regions.

2.2.2 Volume-based Measures of Social Interaction Potential

In this study, we redefine social interaction potential in a region as the weighted average intersection volume across all pairs of individuals in the region. Instead of using the time measurement $\mathrm{A}_{\mathrm{ijqr}}$ that only considers temporal dimension, we use a new measure - V_{ijqr} that considers both spatial and temporal dimension of the prism intersection.

$$SIP = \sum_{i} \sum_{j} \sum_{q} \sum_{r} V_{ijqr} \, P_{ij} P_{qr}, \tag{5}$$

where V_{ijqr} is the theoretical volume of intersection between the space-time prism of an individual who lives in $\mathrm{Z_i}$ and works in $\mathrm{Z_j}$, and the space-time prism of another person who lives in $\mathrm{Z_q}$ and works in Z_r. In this case, SIP is the weighted average volume of all pairs of prism intersections in the region, where the weight of the theoretical volume - V_{ijqr} is the product of two elements in the probability matrix defined by current SIP, P_{ij} and P_{qr}.

When the population is densely distributed in the region and each pair of individuals in the region has larger prism intersections, the value of the SIP metric goes up. Alternatively, when each person's space-time prism is far from others', the SIP metric will be low. Therefore, we could infer that metropolitan areas with high accessibility for each individual and strong population commute centers will have a higher average space-time prism intersection volume and higher SIP metric.

The new SIP metric is bounded by the range [0, *bA*], where *A* is the area of the region. If the time budget is measured in minutes and the area is measured in square kilometers, the units of SIP value will be in minutes × square kilometers. SIP equals the minimum value, 0, when all pairs of individuals have nonintersecting time-space prisms, and SIP equals the maximum value, *bA*, when all pairs of time-space prisms cover the whole study space both in spatial and temporal dimension. This means that all workers could "teleport" to any location in the city after work. In reality, both of these cases are unlikely, but the ratio SIP/bA might be used as a measure of efficiency when comparing SIP between two different cities. This measurement can be explained as the expected average amount of time available for after-work social contact between any two workers at any one location in the region.

The revised SIP metric is defined in 3D continuous space and therefore not subject to the issues of scale and zoning inherent to the modifiable area unit problem. However, it is unrealistic to compute the new theoretical definition of SIP using a real-world dataset. First, it might be difficult to collect the individual level home-to-work journey data, so we could hardly find the exact two vertices for each person's space-time prism. Even if we could, it would be computationally intensive to compute the true volume of each prism intersection V_{ijqr}. One approach to computing an accurate approximation of the true SIP value is to divide the study region into a regular grid, and use the grid centroids to represent the potential social contact locations. Then, by invoking the same principals used in Simpson's approximation to numerical integration, we find that:

$$SIP = \sum_i \sum_j \sum_q \sum_r V_{ijqr} P_{ij} P_{qr} = \lim_{\substack{K \to \infty \\ s_k \to 0}} \sum_i \sum_j \sum_q \sum_r \sum_{\mathrm{k}} A_{ijqr}^k P_{ij} P_{qr} \, s_k \qquad (6)$$

where s_k is the area of each grid cell, and there are Kgrid cells in the region. When the number of regions approaches infinity, and the area of each grid cell approaches 0, our numerical approximation approaches the theoretical value of SIP. Because it is impossible to divide a region into an infinite number of cells, we find two alternative ways to approximate the true SIP value.

One alternative way to approximate SIP is to divide the study region into regular grid cells. We could get an approximation value with higher accuracy when the cell size is smaller. This method might be able to get a high accuracy result, but as the grid cells get smaller and smaller, we need to spend a lot of time to compute travel time matrices and the A_{ijqr}^k terms. Thus, we need to find the optimized resolution for the grid cells in order to find a balance between computational burden and accuracy.

Another alternative approach to approximate SIP is to use census tracts to divide the study region and to assign the area of census tract k in s_k We can save computational time of the travel time matrix by using this method, but we have to test if the accuracy of this approximation of SIP is sufficient. One particularly worrisome outcome is that accuracy in this case will vary over space as the size of census tracts is not constant throughout any given region.

2.2.3 Input Parameters

Computing both the current and volume-based definitions of SIP requires 3 major input parameters: an origin-destination flow matrix, a travel time matrix, and a single, after-work time budget. The travel time matrix used in previous SIP studies assume free-flow travel through the automobile transport network. However, we would like to know whether SIP is impacted by travel delays due to congestion. In order to assess the impact of congestion on SIP, we define a new parameter called the congestion factor as a scalar multiple of all travel times. These input parameters can change the volumes of space-time prisms in a variety of ways. Increasing the time budget results in direct increase of prism volume by increasing the time difference between start and end anchor points. Applying a strong congestion factor constrains the area that individuals are able to travel, which reduces the space time prisms' volume. Moreover, the flow matrix determines the spatial distribution of all prisms in a region and the weight of each prism. We hypothesize that the flow matrix will mediate the effect of changing the time budget and the congestion factor. For example, the effect of congestion on SIP may be stronger in larger more sprawling cities compared to compact ones. Here, the flow matrix is capturing the spatial structure of a region, which in turn may impact parameter sensitivity. Therefore, it is worthy to discover the sensitivity of SIP value to the time budget and congestion factor parameters, while controlling for both compact and sprawling metropolitan settings.

3. METHODS

3.1 Experiment Design

3.1.1 Investigating the Role of Scale in Individual Prism Intersections

The first experiment is designed to determine how the distribution of two individuals' home and work place can influences the approximation accuracy of space-time prisms' intersection volume when using different grid sizes. When two space-time prisms have different shapes and are located in different urban contexts, the patterns of the variation of the approximation accuracy by the increasing grid cells may be different.

In this experiment, we chose combinations of two individuals (i.e., four prism anchor points) from 13 sample points that are stratified throughout the Wasatch Front into different types of neighborhoods: the central business district, inner suburbs, outer suburbs, town centers, and their respective residential areas as well. The locations are shown in Figure 1. This distribution of anchor locations assures that we can get all kinds of shapes of space-time prisms, space-time prisms that cover different types of urban forms, and that variations in distance between prisms are widely accounted for. We investigated grids that covered the entire study region using the following grid cell edge lengths: 1.5km, 2km, 2.5km, 3km, 3.5km, and 4km. In each case, any grid cells that were not within 2 kilometers of the region's street network were removed. This eliminated large wilderness and rural areas on the outskirts of the city.

ID	Spatial Context
1	City Close Suburb
2	City Center
3	City Close Suburb
4	City Far Suburb1
5	City Far Suburb2
6	City Far Suburb3
7	Fringe
8	Small Town Suburb
9	Small Town Center
10	Town2 Center
11	Town2 Suburb
12	Town1 Center
13	Town1 Suburb

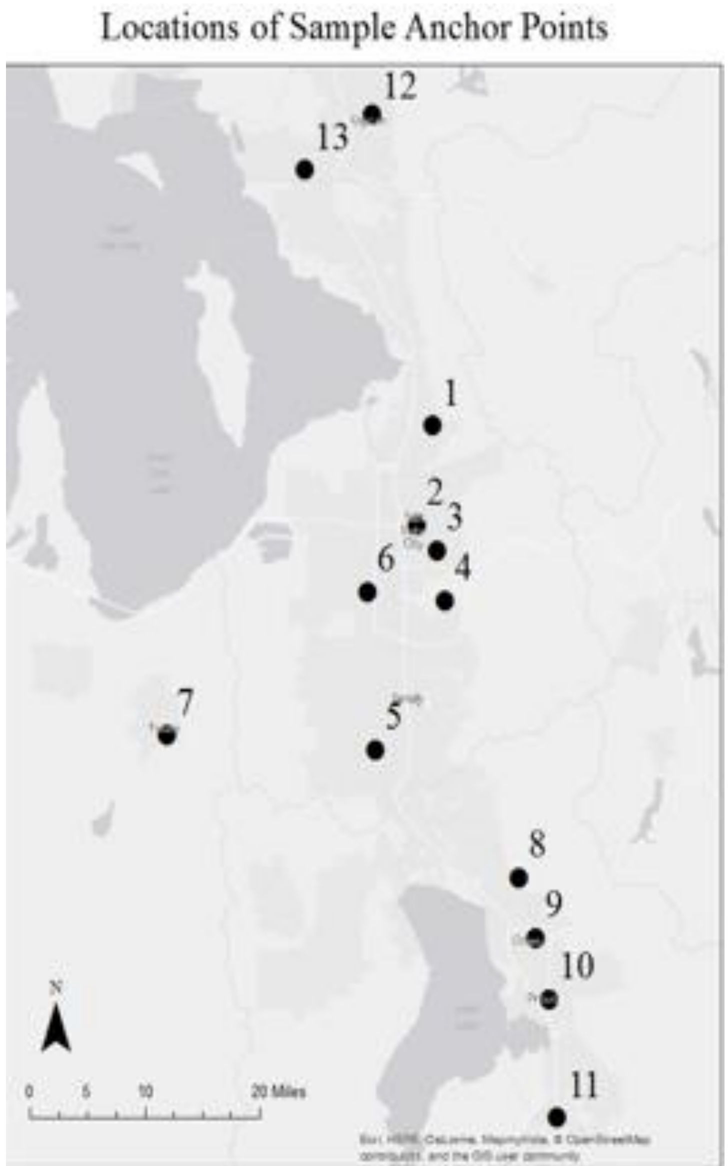

Figure 1 Sample anchor points for the experiment that investigates two individuals

Next, we computed and recorded the approximation of prism intersection volumes between all pairs of prisms using the 6 grid cell definitions. This results in a large number of results, 13^4 unique prism pairs for each grid cell size. To make sense of this vast amount of information, two linear regression models were built to determine the relationship between grid resolution and volume estimation accuracy while controlling for prism sizes and locations. The first explored the trend in accuracy with respect to cell size, and the second is used to explore variance in this trend. In both models, the independent variables were a) prism size, represented by the network travel time between the origin and destination anchor points; b) relative prism locations, represented by the network travel time between anchors of different prisms; and c) absolute locations, measured as distance from anchors to the CBD. With the coefficients of the two linear regression models, we can understand the relative strength and direction of impact that each independent variable has on the relationship between estimation accuracy and grid cell resolution.

Beyond exploring the above relationships, we also use this experiment to identify a cell size that represents a compromise between accuracy and computational burden. To do this, we draw a scatterplot of computation time versus error, where error is calculated as $(A_r - A_{1.5})$ and A_r is the prism intersection volume using resolution r kms. This essentially assumes that intersection volumes estimated with 1.5 km cells are the true intersection volumes, and that scale errors result from using lower resolutions surfaces. An appropriate range of cell sizes is selected via analysis of this plot for future analysis.

3.1.2 Investigating Scale in Accuracy of Total SIP Estimation

In this experiment, we explore the role of scale in the computation of the SIP metric. In theory, the scale-related error in SIP is a result of summing over all individual space-time prism pairs in the region. However, it is unclear how the scale-related errors combine during aggregation. This is because the approximation error of each intersection is not thought to have an expected sign. There may be just as many positive and negative errors, and these may cancel each other out when aggregating over all space-time prisms in a region. This suggests that sufficient accuracy may be achieved for the SIP model at a higher level of spatial aggregation, therefore reducing computational burden. With 8 different cell sizes (with edge length of 1.5km, 2km, 2.5km, 3km, 3.5km, 4km, 5km, and 6km), we conducted an experiment to test how grid size influences the approximation accuracy of total SIP. We assume that if the grid size approaches zero, the SIP approximation will approach the true theoretical SIP, but the computational time will increase. We also determine if we can continue to use the census tract division to substitute grid cell division to get the same accuracy using less computation time. We conducted this experiment using Salt Lake City, Portland, Chicago, and Atlanta, with different urban spatial structures and overall sizes.

Subsequently, using scatterplots showing the variation of errors, we found an optimal resolution of grid cells by balancing the computational burden and accuracy for each city. We also compared the grid-based approach to the weighted census tract approach to see which provide more reasonable estimates.

3.1.3 Investigating Sensitivity of SIP to Other Input Parameters

According to the theoretical definition of Social Interaction Potential, the SIP value depends on the size of the time budget and the velocity of travel along routes. Increasing the time budget and increasing speeds can increase the volume of space time prisms and increase the volume of space-time prism intersections. In order to investigate how these two input parameters can impact SIP values, two sensitivity analyses were conducted. Although the time budget, b, appears directly in the SIP computations, travel speeds find their way into the equations as part of precomputed origin/destination travel time matrices. A new parameter called a congestion factor was defined as a scalar multiple of all travel times.

The analysis in this experiment entailed the computation of SIP values for the four sample cities (Salt Lake City, Portland, Chicago, and Atlanta) using different values of the time budget parameter (from 60 minutes to 180 minutes in 20-minute increments), and multiplying the travel time matrix by different values of the congestion factor (from 0.5 to 3.0 using increments of 0.5). For each parameter, we derived mathematical relationships, elasticity, between the input parameters and the value of SIP using linear regression models. Running the experiment on the four sample cities of different sizes and spatial structures allows us to see if SIP in some types of cities is more or less responsive to changes in the input parameters. Also, as the goal of the broader SIP research project is to rank American cities according to their SIP, we investigated if the order of the SIP value ranking changes when we change these input parameters.

3.2 Implementation

Since computation of SIP is very intensive, this research takes advantage of parallel computing infrastructure at the University of Utah Center for High Performance Computing (CHPC). In particular, custom software was written by a programmer at the CHPC in C using Message Passing Interface (MPI). This enables us to dispatch the task of computing billions of $A^k_{ijqr}P_{ij}P_{qr}s_k$ terms to many CPU cores in parallel, thereby greatly improving runtimes.

3.2.1 Tools

Matlab, ArcGIS Desktop, and computational clusters in the Center for High Performance Computing (CHPC) were used to implement the calculation program of social interaction potential, prepare the input data, run the experiments, and analyze the results. Matlab scripts were used in several parts of the research. For experiment 1, prism intersection volumes were computed in Matlab. However, for experiments 2 and 3, Matlab scripts were only used to transform the input data matrices into the binary data files required by the computational clusters, and transform the resulting binary data files outputted by the CHPC back into Matlab tables for further data analysis. ArcGIS Desktop was used to compute all travel time matrices using its network analysis function. As a GIS tool, it was also used to create maps and visualize some results of the analysis.

Computational clusters in the CHPC, in particular *Ember* with 3144 cores and *Kingspeak* with 832 cores, were used to code, compile, debug, and run the tool for computing the grid-based social interaction potential metric. With the Message Passing Interface, the code breaks down the large computation problem into individual intersection combinations and dispatches them to a large number of CPU cores. The programming work was performed by Wim Cardoen, a research scientist at the CHPC.

3.2.2 Data

The Census Transportation Planning Package (CTPP) 2006-2010 that uses 5-year averages of the American Community Survey (ACS) is the primary data source used in this research. The census tract-level CTPP data provide the home-to-work journey data, which show the total number of workers who live in one specific census tract and work in all other census tracts in each region. This dataset was used to compute the probability matrix, one of the inputs of the current and newly proposed SIP computation methods. After the volume of each pair of space-time prisms intersections is approximated, the probability matrix generated from the CTPP is used to aggregate those volumes together using the probability weighted sum and get a regional-scale measure of social interaction potential.

ESRI Street Map North America network dataset is a detailed SDC format ArcGIS network dataset that records the geocoding and travel speed limit of each street arc and node in North America. It contains 2005 Tele Atlas streets enhanced by ESRI and Tele Atlas before being packaged for distribution. This dataset was used to compute the free-flow travel times between each census tract centroid and regular grid centroid using the network analysis tool box of ArcGIS. The travel time matrix is another essential input of the social interaction potential computation. The building block of social interaction potential metric, which is the available time that two individuals can coexist in a location, was computed using the elements in the travel time matrix.

4. RESULTS

This section focuses on the findings of our three experiments. First, we present the results of experiments investigating the effect of grid resolution on individual prism intersection volumes. Next, we look at the relationship between scale and total SIP calculations. Finally, we present a sensitivity analysis of SIP with respect to several of its other input parameters.

4.1 Experiment that Investigates Two Individuals

For this experiment, time-space prisms are simulated, and prism intersection volumes are computed using a selection of different sized grids. The aim is to determine the relationship between computation error and cell size, and to find an optimum grid cell size to use in big batch SIP computations

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4.1.1 Descriptive Statistics of Stability and Trend

We performed a descriptive analysis to investigate the trend and stability of prism intersection estimations for pairs of prisms over different cell resolutions and different prism anchor points in Salt Lake City. In Table 1, we find that the overall area of accessible locations represented by the grid is consistent between the grid resolutions. This ensures that the intersection volumes we estimated for each grid cell resolution are comparable.

Table 1 The area of accessible locations for each grid resolution

CELL EDGE LENGTH (KM)	CELL AREA (KM^2)	NUMBER OF K LOCATIONS	TOTAL AREA (KM^2)
1.5	2.25	9251	20815
2	4	5221	20884
2.5	6.25	3320	20750
3	9	2332	20988
3.5	12.25	1695	20764
4	16	1301	20816

In total, we investigated 13^4 pairs of prisms. For each pair, we estimated the prism intersection volume on grids with 6 different resolutions and then calculated the standard deviation of intersection volumes. The standard deviation, SD_p, is a measure of the stability of the intersection volume estimates over different resolutions. Here, the p indicates that the statistic is generated for each pair of prisms. We have:

$$SD_p = \sqrt{\frac{\sum_{r=1}^{R}\left(V_{pr} - \bar{V}_p\right)}{R-1}}$$

where r is a grid cell resolution, R is the total number of resolutions tested, V_{pr} is the calculated volume of the prism intersection for pair p using resolution r, and $\bar{V}_p$ is the mean prism volume intersection for pair p computed across all resolutions. This is a measure of overall variation in estimation volume for a given prism pair.

We also calculated a linear regression slope, β_p, of the intersection volume versus the grid cell area. While a linear trend may not be the best fitting specification, it is selected for its ease of interpretation and reproducibility over the large number of prism pairs. For instance, for a sample intersection of a pair of prisms shown by the scatter plot in Figure 2, β_p is the slope of the regression line and SD_p is shown by the standard deviation of the point's vertical axis values.

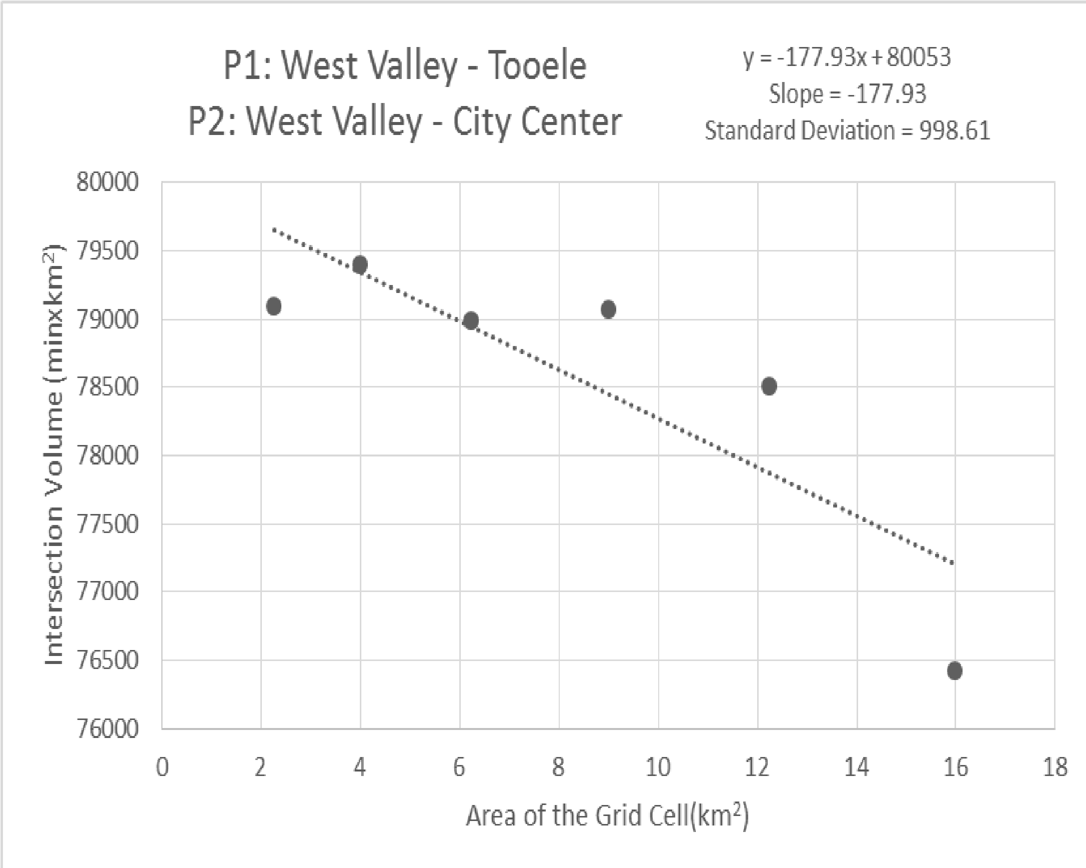
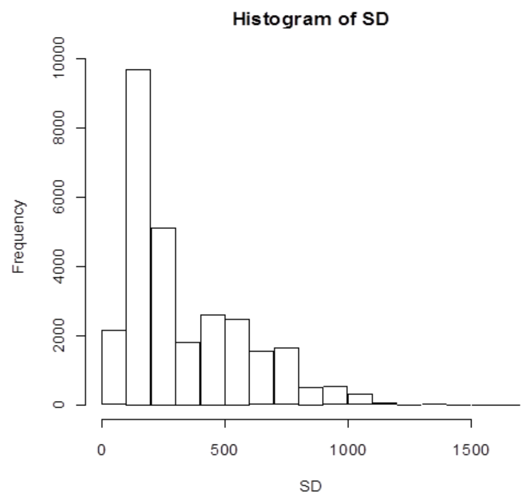


Figure 2 The scatter plot of the prism intersection volume versus the resolution for a sample pair of prisms: Sample of intersection of the prism of person 1 (town center to town center) and the prism of person 2 (town center to city center)

Table 2 presents descriptive statistics for SD_p and β_p. It is evident that approximation stability and trend both vary quite drastically. The complete distributions are depicted in histograms in Figure 3. We see that most pairs have small standard deviations, which is shown by the positive skew in the standard deviation distribution. We also find that most of the regression slopes are negative, which indicates that underestimation occurs with larger grid cells for most of the situations. Given such a large degree of variability in stability and trend, we would like to better understand the relationships of these statistics with respect to the absolute and relative spatial configurations of the space time prism pairs.

Table 2 Descriptive statistics of stability index (SDp) and trend index (β_p)

	$\boldsymbol{SD_p}$ (MINUTE×KM^2)	$\boldsymbol{\beta_p}$
MEAN	339	-40
MEDIAN	232	-25
STANDARD DEVIATION	244	43
MINIMUM	23	-209
MAXIMUM	1659	113
COEFFICIENT OF VARIATION	0.72	-1.08



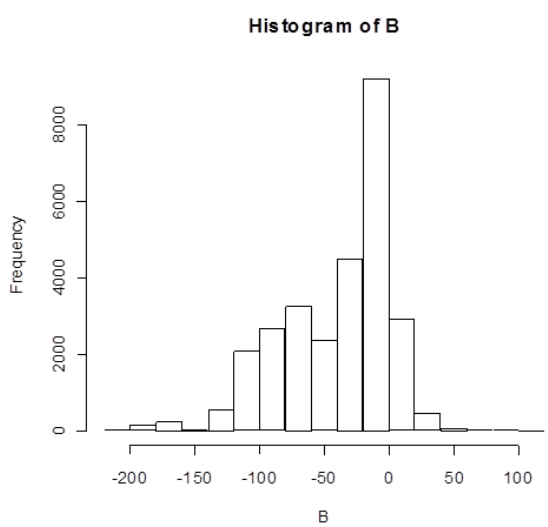


Figure 3 Histogram of stability index - SD_p and trend index - β_p

4.1.2 Stability, Trend, and Spatial Characteristics of Space-time Prisms

We used linear regression models to investigate the relationship between the stability and trend of intersection volumes, and the spatial characteristics of the two prisms. We are interested in how stability and trend are impacted by a) the locations of the prism anchors with respect to the CBD, b) the skewness of the prisms, which is described by the travel time from the start anchor point to the end anchor point, and c) the proximity of the prisms to each other. These measures were all computed in a GIS using network analyst and grid-based area calculations. Regression results for the two dependent variables, SD_p and β_p, appear in Table 3.

The first column in Table 3 provides the regression results for SD_p. The model has a medium level of fit, with an adjusted R^2 of 0.5478. All of the coefficients are highly significant ($p < 0.01$) and negative, indicating that stability is achieved when space time prisms are smaller and when pairs of prisms are farther apart. This makes sense because these more stringent constraints result in thinner prism intersections and, therefore, less "room" for variability.

The second column in Table 3 provides the regression results for β_p. The adjusted R^2 of this model is 0.2927, indicating that much of the variance in the trend statistic is left unexplained by the model. Despite this, all of the coefficients are highly significant. The results indicate regression slopes are more negative for larger prisms, and more positive when prisms are farther away from each other. In other words, when intersection volumes are smaller, we tend to find increased stability in estimation with respect to cell size.

Table 3 Regression results for stability and trend

INDEPENDENT VARIABLES[a]	COEFFICIENTS FOR $\boldsymbol{SD_P}$	COEFFICIENTS FOR $\boldsymbol{\beta_p}$
SKEWNESS OF PRISM 1	-0.541***	-0.021**
SKEWNESS OF PRISM 2	-0.529***	-0.022**
TRAVEL TIME BETWEEN ORIGINS	-2.240***	0.134***
TRAVEL TIME BETWEEN DESTINATIONS	-2.422***	0.203***
ORIGIN 1 TO CBD	-2.604***	0.654***
DESTINATION 1 TO CBD	-2.646***	0.669***
ORIGIN 2 TO CBD	-2.610***	0.654***
DESTINATION 2 TO CBD	-2.653***	0.670***
CONSTANT	961.75***	-142.9***
ADJUSTED $\boldsymbol{R^2}$	0.5478	0.2927
$\boldsymbol{N}$	13^4	13^4

[a] all variables measured in minutes

* indicates significance at the 0.10 level

** indicates significance at the 0.05 level

*** indicates significance at the 0.01 level

4.1.3 Computation Time and Volume Error

Figure 4 shows a scatter plot of computation time versus total error of volume estimation. To calculate error, we assume that intersection volumes estimated with 1.5 km cells are the true intersection volumes. Thus, the vertical axis is:

$$\sum_{p\in P}\sum_{g\in G}\left(V_{pg} - V_{p1.5}\right)$$

where p is a specific pair of prisms, P is the total set of pairs, g is a specific grid cell resolution, and G is the total set of resolutions tested.

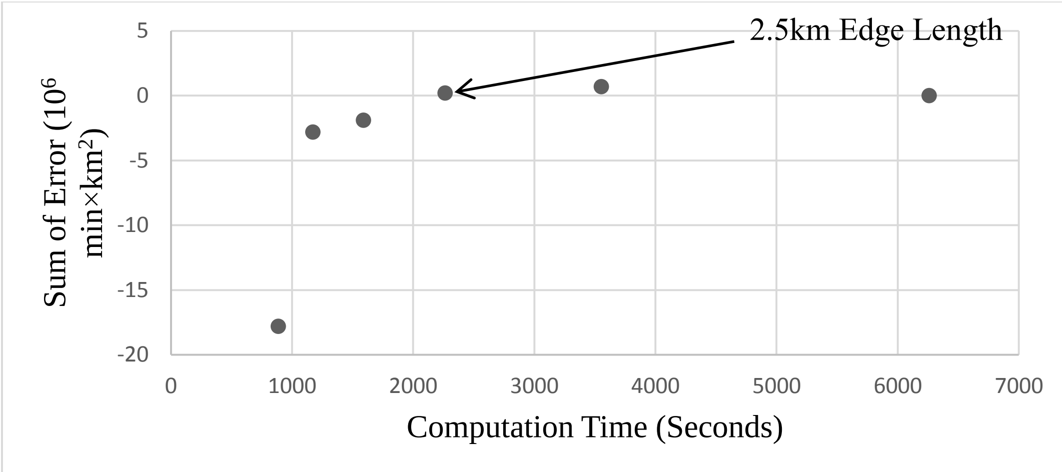


Figure 4 Scatter plot of computation time versus sum of errors

The figure shows that errors are large and negative for larger cell sizes and shorter computation times. Errors tend to stabilize for cells of 2.5 km size and smaller. Thus, it may not be worth the computational burden to estimate SIP using grid cells smaller than 2.5 km. We can conclude that a spatial grid using 2.5 km cells is a reasonable balance between computational burden and the precision of volume intersection estimation. This result, while providing us with a preliminary suggestion for the cell size to use in estimating SIP, may be limited to the study area used in this experiment (Salt Lake City), and the limited number of prism combinations tested. In the next experiment, we endeavor to discover whether the findings hold when transferred to more study areas and for the complete set of computations required by a full SIP calculation.

4.2 Experiment that Investigates Total SIP

In this experiment, we extend our investigations to encompass the complete SIP calculation in multiple study areas. We hope to find out whether a 2.5 km cell size performs with minimal error in multiple cases. Based on the results of the last experiment, aggregated SIP values were computed for Metropolitan Planning Organizations of Salt Lake City (Wasatch Front Regional Council and Mountainland Association of Governments), Portland (Portland Metropolitan Planning Organization), Atlanta (Atlanta Regional Commission), and Chicago (Chicago Metropolitan Agency for Planning) using 8 different cell sizes (1.5km, 2km, 2.5km, 3km, 3.5km, 4km, 5km, and 6km). The origin destination matrices used in this experiment were drawn from the CTPP 2006-2010 part 3 journey-to-work flow data. Free-flow network travel time matrices between population weighted centroids and grid cell centroids were constructed in ArcMap using the SteetMap North America network dataset. And SIP metrics were computed using 2 nodes (24 cores) of the Ember cluster computer at University of Utah CHPC.

For each city and grid cell size, we computed the total SIP using the equation $\sum_i \sum_j \sum_q \sum_r \sum_{\mathrm{k}} A_{ijqr}^k P_{ij} P_{qr}\, S_k$ using grid representation. We also computed area weighted SIP and traditional SIP using equations $\sum_i \sum_j \sum_q \sum_r \sum_{\mathrm{k}} A_{ijqr}^k P_{ij} P_{qr}\, S_k$ and $\sum_i \sum_j \sum_q \sum_r \sum_{\mathrm{k}} A_{ijqr}^k P_{ij} P_{qr}$ using census tract representation for comparison. We control the total grid area by dividing SIP by the area on which its calculations are based. We then compute error as the percentage difference to the SIP calculated using the 1.5km grid, the smallest cell size used in our experiments.

Table 4, Figure 5, Table 5, Figure 6, Table 6, Figure 7, Table 7, and Figure 8 show tabular and graphical results for each city. The results show that grid-based SIP calculations produce rather small errors while grid cells remain small. While results are sometimes more accurate using even larger cell sizes up to 3.5 or 4 km, in adherence with best practices with respect to scale effect of MAUP, we choose to move forward with as

Table 4 Comparison of SIP calculations for Salt Lake City

Cell edge length (km)	K	SIP (minute×km^2)	SIP/Area (minutes)	CPU Time (seconds)	SIP/Area Error (minutes)
1.5	2719	27860	4.554	260	0.0000
2	1509	27699	4.589	153	0.0351
2.5	955	27341	4.581	102	0.0269
3	682	28338	4.617	74	0.0630
3.5	496	27665	4.553	55	-0.0007
4	379	27117	4.472	43	-0.0821
5	237	26850	4.532	26	-0.0222
6	163	27431	4.675	18	0.1208
Area Weighted	440	36594	6.000	54	1.4500
Traditional	440	353830		54	

small a grid cell as is computationally feasible. In this case, since errors tend to stabilize at 2.5 km, we propose the use of this resolution when computing SIP for American cities.

We can also use these results to compare the grid-based methods of computing SIP to those based on census tracts. There are two versions of the latter, one that uses the area-weights, and one that ignores area sizes altogether. The results computed through the area-weighted approach have the same magnitude as the results computed through the grid-based method, which indicates that they are comparable, unlike the traditional results that might have been exaggerated by not controlling for area. However, results of the area-weighted method still got a larger error even compared with results of the grid-based method that has a smaller computational scale, especially for smaller cities like Salt Lake City and Portland. The reason for the error is that census tract centroids usually have high transportation accessibility. So using the area-weighted method that uses census tract centroid to represent the social interaction locations causes overestimation of the average social interaction time by assuming that all locations in the census tract have the same level of accessibility as the census tract centroid.

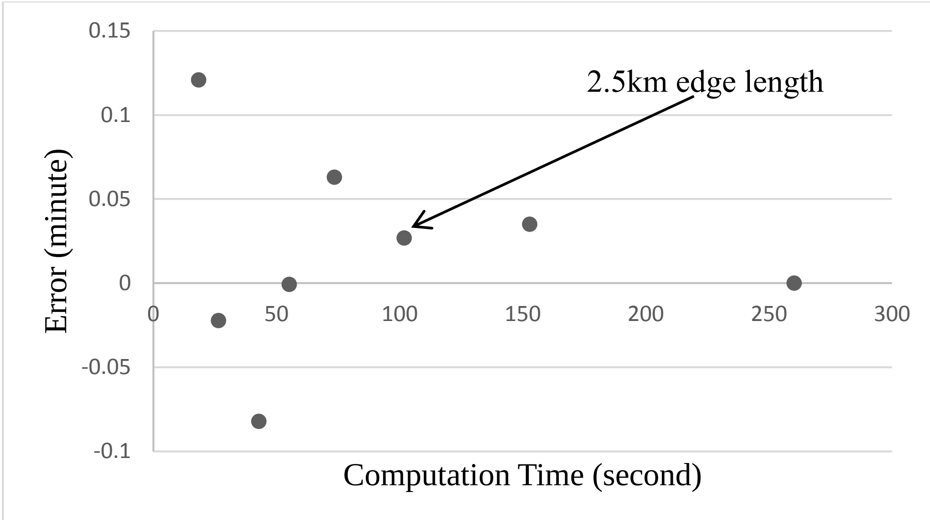


Figure 5 Error versus computation time for Salt Lake City

Table 5 Comparison of SIP calculations for Atlanta

Cell edge length (km)	K	SIP (minute×km^2)	SIP/Area (minutes)	CPU Time (seconds)	SIP/Area Error (minutes)
1.5	5369	36259	3.001	2925	0.0000
2	3011	36112	2.998	1695	-0.0031
2.5	1930	36269	3.007	1125	0.0053
3	1342	36275	3.003	806	0.0019
3.5	975	36408	3.048	602	0.0468
4	757	36026	2.974	473	-0.0271
5	487	36100	2.965	300	-0.0364
6	340	35568	2.906	232	-0.0956
Area Weighted	872	35446	2.934	760	-0.0672
Traditional	872	7088		760	

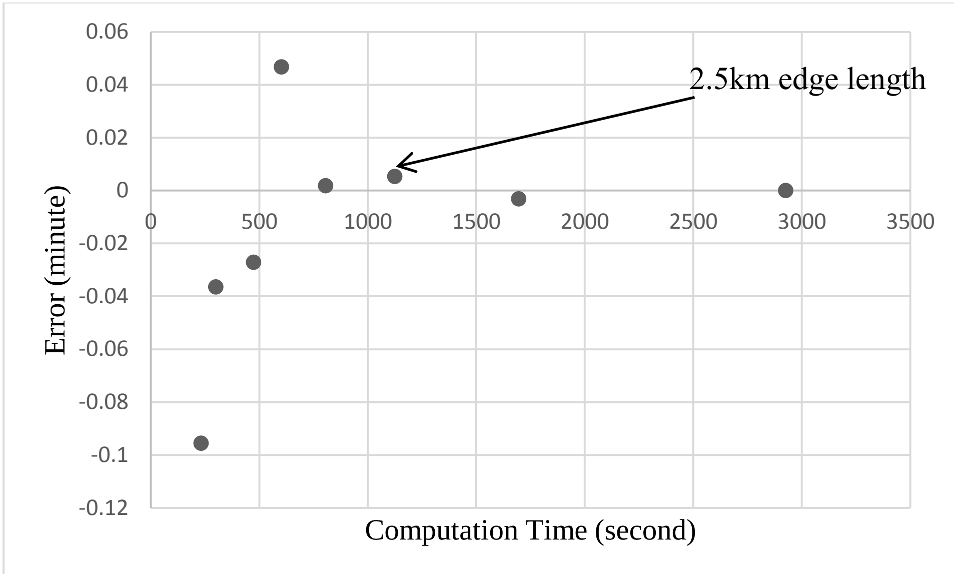


Figure 6 Error versus computation time for Atlanta

Table 6 Comparison of SIP calculations for Chicago

Cell edge length (km)	K	SIP (minute×km^2)	SIP/Area (minutes)	CPU Time (seconds)	SIP/Area Error (minutes)
1.5	4712	44375	4.185	12893	0.0000
2	2689	44164	4.106	7593	-0.0795
2.5	1695	44358	4.187	5033	0.0017
3	1177	44061	4.159	3586	-0.0260
3.5	863	44137	4.175	2702	-0.0105
4	659	44515	4.222	2144	0.0364
5	419	43910	4.192	1449	0.0064
6	292	42840	4.075	1025	-0.1101
Area Weighted	1968	44069	4.134	9159	-0.0518
Traditional	1968	23163		9159	

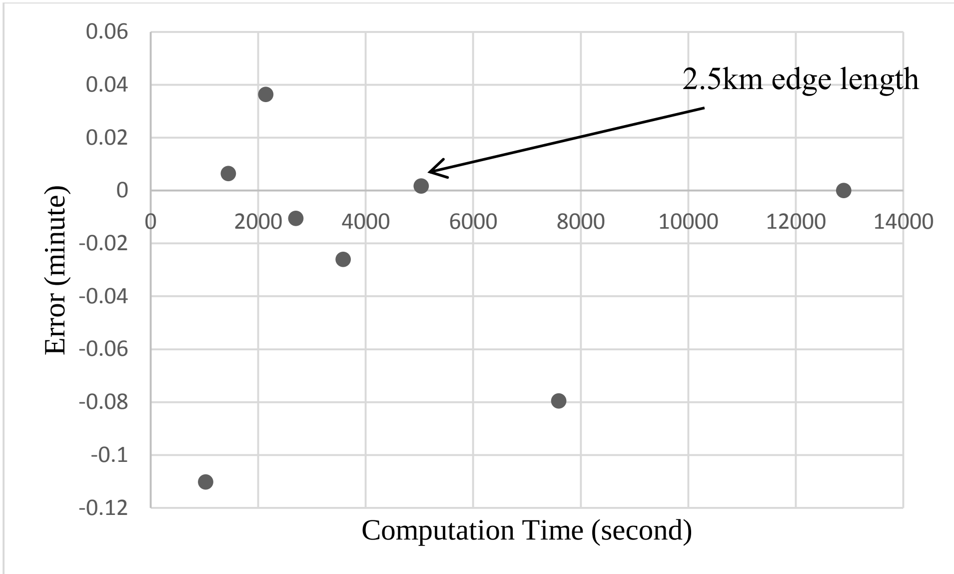


Figure 7 Error versus computation time for Chicago

Table 7 Comparison of SIP calculations for Portland

Cell edge length (km)	K	SIP (minute×km^2)	SIP/Area (minutes)	CPU Time (seconds)	SIP/Area Error (minutes)
1.5	1247	59094	21.062	100	0.0000
2	694	58892	21.215	56	0.1529
2.5	450	59065	21.001	37	-0.0609
3	303	58173	21.332	26	0.2706
3.5	231	58728	20.754	20	-0.3081
4	177	59766	21.104	16	0.0422
5	109	55843	20.493	10	-0.5691
6	74	56905	21.361	6	0.2991
Area Weighted	331	70301	25.311	34	4.2491
Traditional	331	13079		34	

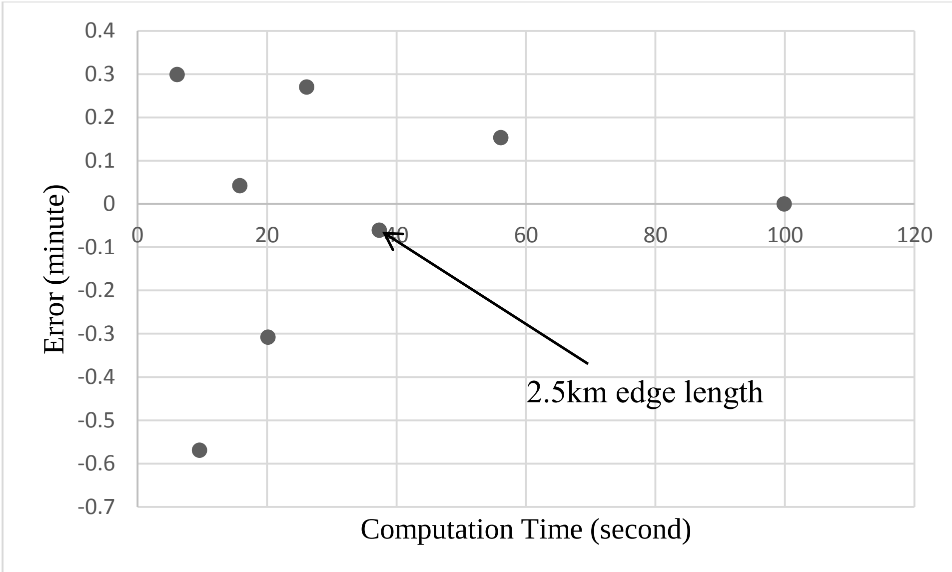


Figure 8 Error versus computation time for Portland

4.3 Sensitivity Analysis

In this experiment, we fixed the grid resolution to 2.5 km and explore the sensitivity of SIP to two other input parameters, time budget and travel times. We explored time budgets from 60 minutes to 180 minutes in 20-minute increments. To address travel times, we introduced congestion factors of 0.5 to 3.0 using increments of 0.5. The congestion factors multiply the travel time matrices in order to explore how congestion might impact SIP calculations. In particular, since congested travel times are far more difficult to compute in comparison to free flow times, we are curious to see how ignoring congestion affects the ordering of SIP values across different cities.

Table 8 provides some basic descriptions for the four sample cities. Portland and Salt Lake City are relatively small areas with higher population density values and shorter commute time values. People in Atlanta and Chicago have to spend a longer time to go to work by living in a larger city with a lower density value. SIP values for large cities are

Table 8 Descriptive data of the four cities

CITIES	STUDY AREA (KM^2)	WORKER DENSITY ($WORKERS/KM^2$)	MEAN COMMUTE TIME (MINUTES)
Portland	2778	254	12.1
Salt Lake City	6099	148	14.9
Atlanta	12080	58	21.5
Chicago	10661	66	17.5

expected to have different sensitivity to input parameters compared with SIP values for small cities, which are caused by the different types of space-time prism distributions.

SIP scores were computed for all combinations of input factors for the four cities. Linear regression models are used to explore the relationship between input parameters (logarithm of time budget and congestion factor) and the logarithm of the four cities' 2.5 km grid-based SIP. Logarithms of SIP were selected because SIP for each city is a highly skewed variable that needs logarithm transformation to transfer it into one that is more approximately normal. Logarithms of time budget were used to allow us to compare the coefficients of time budget and congestion factor in terms of elasticities. As expected, the results shown in Table 9 indicate that time budget has a positive impact on SIP, but congestion factor has a negative impact on it. We also found that time budget has relatively stronger effects on SIP by comparing the coefficients of the two parameters.

It is hard to use the coefficients in Table 9 to compare the effectiveness of input parameters. So we applied an equivalent change to both of the input parameters for all of the four sample cities: we halved the time budget from 120 minutes to 60 minutes and compared this to a doubling of the congestion factor from 1 to 2. The percentage change in SIP value is shown in Table 10. Comparing the percentage change between the two

Table 9 Regression model exploring SIP sensitivity to time budgets and congestion factors

VARIABLE	PORTLAND	SALT LAKE CITY	ATLANTA	CHICAGO
Intercept	-7.28***	-9.18***	-13.83***	-10.46***
log(Time Budget)	3.9***	4.3***	5.54 ***	4.77***
Congestion	-1.6***	-1.99***	-2.79***	-2.36***
R^2	0.9305	0.963	0.9624	0.9671
N	42	42	42	42

* indicates significance at the 0.10 level

** indicates significance at the 0.05 level

*** indicates significance at the 0.01 level

parameters, we see that the estimated SIP values are more sensitive to time budgets and less sensitive to congestion factors. Comparing the percentage of change between cities, we find that the larger cities, Atlanta and Chicago, are more strongly impacted by both input parameters, especially for the congestion factor. This is likely because people's space-time prisms in larger cities are more sparsely distributed, thus the reduction of time budgets, or especially, the increase in travel times, cuts the number and size of prism intersections very drastically. On the other hand, in smaller cities, where prisms are closer together, a reduction in budget or an increase in travel time does not make it impossible for people to interact, it only limits the time available. To help with this explanation, imagine the city where all people live and work at the same location. SIP for this city would be insensitive to travel times because no travel is required. Also, the SIP in the

Table 10 Percentage change in SIP when applying equivalent changes to input parameters

Portland	-93%	-80%
Salt Lake City	-94%	-86%
Atlanta	-98%	-94%
Chicago	-96%	-90%

region would be directly proportional to the time budget parameter, since all interactions are still possible for any possible time budget. For larger cities though, where people are more spread out over space, since SIP so much more depends on travel, these cities are also more sensitive to congestion. In addition, the difference of the time budget's impact on SIP value between cities is small, but there is a large difference of congestion factor's impact on SIP values between cities. The SIP values of big cities with longer commute time are much more sensitive to congestion factor compared with small cities with shorter commute time. Because increasing congestion factor can easily make it impossible for the people with longer commute time to interact with others. This effect may cause the ranking of SIP values to be unstable after we change different input parameters. Thus, we also conducted an analysis for the ranking stability.

Because each city is differentially impacted by the input parameters, it is important to consider the ranking stability after the input parameters change. For each combination of input parameters, the cities are ranked in ascending order according to their achieved SIP levels. Table 11 shows the ranking for each city for each time budget, averaged across the different levels of congestion. Similarly, Table 12 shows the ranking for each congestion factor, averaged across all time budget levels.

Table 11 Average ranking in ascending order of SIP for each city for each time budget

TIME BUDGET	PORTLAND	SALT LAKE CITY	ATLANTA	CHICAGO
60	1.33	2.50	3.67	2.50
80	1.33	2.67	3.33	2.67
100	1.50	2.67	3.33	2.50
120	1.83	3.00	3.00	2.17
140	1.83	3.00	3.00	2.17
160	1.83	3.33	2.67	2.17
180	2.17	3.50	2.50	1.83
OVERALL AVERAGE	1.69	2.95	3.07	2.29
STANDARD DEVIATION	0.29	0.34	0.38	0.26

The variation in rankings indicate that the rankings are fairly stable with respect to time budget but less so for congestion factors. Average rankings of small cities slip slightly when time budgets increase. However, rankings for small cities tend to increase quite rapidly as congestion gets worse and worse. As hypothesized earlier, this is because larger cities with spatially sparse prisms are more dependent on faster travel to achieve SIP than are smaller cities, where distances needed to be traversed are much smaller. Moreover, for the very large cities, when travel speeds and time budgets are increased, this enables the very large numbers of distantly located intersections to occur, therefore contributing very highly to opportunity for social interaction. This is evident from Table 13, the full listing of rankings for each combination of input parameters.

Table 12 Average ranking in ascending order of SIP for each city for each congestion factor

CONGESTION FACTORS	PORTLAND	SALT LAKE CITY	ATLANTA	CHICAGO
0.5	3.71	3.29	1.14	1.86
1	2.14	3.86	2.29	1.71
1.5	1.29	3.29	3.29	2.14
2	1.00	2.86	3.71	2.43
2.5	1.00	2.29	4.00	2.71
3	1.00	2.14	4.00	2.86
OVERALL AVERAGE	1.69	2.95	3.07	2.29
STANDARD DEVIATION	0.99	0.60	1.04	0.42

Table 13 Ranking in ascending order of SIP for each time budget, congestion factor, and city

Time Budget	**Congestion**	**Portland Ranking**	**SLC Ranking**	**Atlanta Ranking**	**Chicago Ranking**
60	0.5	3	4	2	1
60	1	1	3	4	2
60	1.5	1	2	4	3
60	2	1	2	4	3
60	2.5	1	2	4	3
60	3	1	2	4	3
80	0.5	3	4	1	2
80	1	1	4	3	2
80	1.5	1	2	4	3
80	2	1	2	4	3
80	2.5	1	2	4	3
80	3	1	2	4	3
100	0.5	4	3	1	2
100	1	1	4	3	2
100	1.5	1	3	4	2
100	2	1	2	4	3
100	2.5	1	2	4	3
100	3	1	2	4	3
120	0.5	4	3	1	2
120	1	3	4	2	1
120	1.5	1	4	3	2
120	2	1	3	4	2
120	2.5	1	2	4	3

Table 13 Continued

Time Budget	Congestion	Portland Ranking	SLC Ranking	Atlanta Ranking	Chicago Ranking
120	3	1	2	4	3
140	0.5	4	3	1	2
140	1	3	4	2	1
140	1.5	1	4	3	2
140	2	1	3	4	2
140	2.5	1	2	4	3
140	3	1	2	4	3
160	0.5	4	3	1	2
160	1	3	4	1	2
160	1.5	1	4	3	2
160	2	1	4	3	2
160	2.5	1	3	4	2
160	3	1	2	4	3
180	0.5	4	3	1	2
180	1	3	4	1	2
180	1.5	3	4	2	1
180	2	1	4	3	2
180	2.5	1	3	4	2
180	3	1	3	4	2

5. DISCUSSION AND CONCLUSIONS

This research redefines the SIP metric for metropolitan regions, suggests a 2.5 km grid implementation of the new definition, and tests its sensitivity to grid resolution, time budget, and travel speeds. The new definition of SIP fixes the problem of the metric's dependence on the aggregation and the scale of spatial divisions used to represent activity locations in the region. Thus, researchers are able to compare the SIP values for different regions that have different aggregation patterns and scales.

During the process of selecting a better spatial representation to implement our new definition, we found that the computational estimations of SIP varies when we change the shape of representation from census tract to grid cells, or alters the size of the grid cells, which demonstrates the aggregation and the scale effects of MAUP, respectively. To circumvent these two types of MAUP problems, we computed SIP values for both various sizes of grid representation and census tract representation, and found the new implementation of SIP that balanced error and computation time; the 2.5 km grid implementation appears to be largest grid cell size that achieves suitably accurate volume estimates. In particular, both of the experiments we conducted for two individuals and total SIP show that 2.5 km balances between computational burden and estimation accuracy, which shows that the errors will not be canceled by computing a weighted average. Therefore, if we plan to test a new spatial representation in the future, it is worthy to repeat the first experiment - but not the second - to explore the range of the representation's scale for experiments that investigate total SIP. As a possible reference for policy makers, the sensitivity analysis of the input parameters also improves our understanding of the effect of congestion and commuting duration on the social interaction potential of a region. We found that changing the congestion factor and time budget can affect the values and rankings of SIP, but the effectiveness of the impact depends on the city scale, population density, and commute duration. The analysis that investigates the impact of the two parameters shows that time budget has a stronger impact compared to the congestion factor, and the SIP values of larger cities are more sensitive to input parameters, which recommends that increasing the after-work time budget for the large cities would be a more effective way to encourage people to have more overall face-to-face social interaction opportunities. The analysis also shows that SIP values' sensitivity to congestion factor highly depends on the commute duration of the city. According to the ranking stability analysis results, we also suggest that the ranking of SIP value for cities with extremely short/long commute time can be increased/decreased by reducing the congestion of the cities. Therefore, maintaining an uncongested street network is essential for cities with extreme commute duration to compete SIP values with other cities.

However, because of the time limit, only four sample cities were used to analyze the sensitivity of the new SIP to input parameters. Therefore, we do not have a quantitative analysis for the impact of work density, city size, and street accessibility on the effectiveness of changing input parameters. In future study, more sample cities can be included to validate our conclusions of how distributions of prisms affect the SIP sensitivity.

The new SIP definition and assumptions proposed by this paper are also flexible and we could easily make modifications to make them fit into a scenario closer to reality. If we have enough data sources for loosening the assumptions, we can apply different time budgets and travel time congestion factors for different cities based on the data of American Time Use Survey and traffic congestion statistics. Or for one city, we can evaluate the SIP outcome of upgrading the traffic condition for part of the transportation system by updating the new input distance matrix. The metric can also be modified to consider the nonautomobile trips by loosening the vehicular transportation assumption. Social activities can be considered to happen during the public transit trips for the cities with strong transit systems. For the new definition, we assume that all the locations inside the city have the same opportunity for people to consider them as social interaction locations. However, in reality, people prefer to use high-density locations with more shops, cinemas, restaurants, parks, houses, and transportation accessibilities to interact. And our disaggregate SIP values can also help us to predict the potential interaction locations, which might attract investors to build new interaction facilities. Our SIP, together with new spatial social-economic parameters that describe interaction attractiveness of each location, can be integrated into an iterative land use model to provide decision support for the investment of public facilities for social activities.

The SIP software package developed in this research can also be applied to many interesting future investigations by computing SIP values for many cities. For empirical studies of the new SIP, we could use statistical methods to link SIP values to indicators of urban structure that affects the space-time constraints of the activities inside the city. And for the calibration and validation of the new SIP values, we could also use social activity data to validate the SIP value for some specific study areas, and build equations to predict the quantity/duration of face-to-face social interaction simply by the commute data and transportation OD matrix. With the data, we might also be able to investigate the relationship between social interaction potential and other factors such as creativity, innovation, equity, and social segregation.

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